Short-term load forecasting of the distribution system using cuckoo search algorithm

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ABSTRACT

For solving the different optimization problems, the cuckoo search is one of the best nature's inspired algorithms. It is an effective technique compare to other optimization methods. For this manuscript, we are using a back propagation neural network for the Xintai power plant consist of short-term electrical load forecasting. The limitation of back propagation is overcome by the cuckoo search algorithm. The function is used for cuckoo search is Gamma probability distribution and its result is compared with other possible cuckoo search methods. The mean average percentage error of Gamma cuckoo search is 0.123%, cuckoo search with Pareto based is 0.127% and Levy based cuckoo search is 0.407%. Other results of the cuckoo search are also found by a linear decreasing switching parameter with a mean average error is 0.344% and 0.389% of mean average error with the use of an exponentially increasing switching parameter. This improved cuckoo search algorithm brings good results in the predicted load which is very important for the Xintai power plant using short-term load forecasting.

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1. INTRODUCTION

For a given problem, the optimal solution is obtained by a systematic procedure which is known as optimization [1]–[3]. It is used for the solution of maximum and minimum value of a problem and it is called cost function or objective function. There are two types of optimization problems, i.e., constrained and unconstrained problems. For the solution of all subsets, constrained problems are using and for all viable solutions, unconstrained functions are using [4]–[6]. Now a day, the optimization technique is adopted by different areas but not limited to specific systems. Like the transmission of electricity with a minimum loss, design of the system, operation of an electric circuit, generation of electricity and wireless communication routing. So, suitable optimization is required for the calculation of the computation time, converge rate and minimum or maximum value accurately [7], [8].

Nature's inspired algorithm is constructed by the researcher with the inspection of the behavior of animals. For the calculation of the distance between a bat and its surrounding, the researchers are using a bat-inspired algorithm [9]. This technique is also used for the calculation object in frequency tuning. Similarly, another nature's inspired algorithm is particle swarm optimization (PSO) where the fishes and birds are searching for their food considered as a potential solution in PSO [10]. In this technique, the animals are searching for food and they communicate the food to the rest of the group when the food source is found. Here, the food source is considered as the best solution for the processing of food among groups.

For the calculation of storm and prince, the differential evolution (DE) algorithm is using based on a population vector. This population vector consists of the size of the population which does not change during the searching process and uniform probability distribution. The different parameters are affecting the growth of the population i.e. mutation (new generation), crossover (increasing of diversity) and selection (finding of new solution). It is a robust and efficient process used for continuous space [11]. The behavior of foraging is used by Ant and Bee algorithm which is known as a chemical messenger. It is also known as pheromone [12]. For global optimization, the use of nature's inspired algorithm is simulated annealing (SA). This technique finds a good solution as compared to the limited time constraint of the global solution [13].

The other nature's inspired algorithm is the cuckoo search (CS) algorithm which depends on the reproduction of the kids to increase the population [14]. But, this algorithm is good as compare to other algorithms because the other algorithms like DE, SA and PSO are derived from the CS algorithm has potential random walk and makes the balance between local and global search as compared to SA and GA [14]. The CS algorithm is better than the DE algorithm in terms of convergence speed and finding a good solution [15]. The computational efficiency of the CS algorithm is also good as compared to the PSO algorithm. The CS algorithm is also used in the smart grid for the minimization of loss of real power by control of fault and variation of voltage with allowable level [16]. So, with the consideration of time from one hour to one week, short term load forecasting (STLF) is using in industries. It is used for the planning and maintenance of power networks [17]. The factors which affect the STLF are considered for its work in [18].

The research gap from the above study is the old techniques are bringing poor results in STLF in past. So, in this manuscript, the research gap is fulfilled by the application of different distribution of cuckoo search algorithms in STLF which removes the disadvantages of old techniques. The other parts of this manuscript are arranged as follows: section 2 gives the simulation of STLF. Section 3 presents results and discussions of the work. At last, the conclusion of the work is represented by section 4.

2. STLF SIMULATION

It brings the results of the forecasted load in STLF. After that, the forecasted load will compare with the actual load. Then, we applied the mean absolute percentage error (MAPE) to calculate the error in the forecasted load as given in (1).

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{Actual\ load - forecasted\ load}{Actual\ load}\right) \times 100 \tag{1}$$

Where N is total number of the data set.

2.1. Collection of data

The historical data is collected from the Xintai power plant in the year 2016 from the date of 6.10 to 6.30. The data set is divided into three parts i.e. training, validation and testing as in [19]. Here sunny day is expressed by 0, cloudy day by 0.5 and rainy day by 1.

2.2. Pre-processing of data

The transfer function depends on the input value. If the input value is very large, then the output value does not contain the actual value. So it is avoided by set-up the normalized value within the range of [0, 1] using the minimap function in MATLAB 2015 software package. The processing data is also considered for the missing data.

2.3. Simulation result

The STLF using a feed-forward neural network (FFNN) [20]–[23] is shown in Figure 1. It contains 4 inputs, 25 hidden layers and one output layer with a transfer function. Here, the sigmoid function is used as a transfer function. Figure 1 explains the process of the data transformation from the input layer to the output layer through hidden layers. It also helps in the prediction of the forecasted load. The hourly based load is forecasted at the output of NN [24] uses Levenberg-Marquardt [25] back propagation for the training and forecasts.

Figure 2 shows the flow chart of a hybrid Levenberg-Marquardt. It is good as compared to Levenberg-Marquardt BP. Because BP [26]–[29] able to finds the minimum but it will not able to find the global minima in test function or loss. Figure 2 explains that, the feasibility solution of the forecasted load [30]–[32]. It helps in the removal of the disturbance signal present in the data set for the smooth train of FFNN.

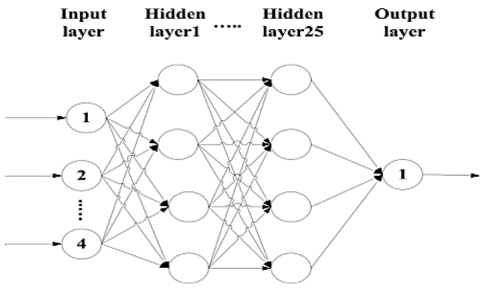


Figure 1. FFNN with BP

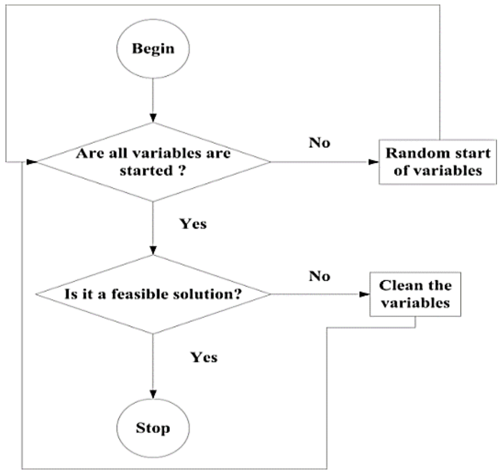


Figure 2. Flow chart of hybrid Levenberg-Marquardt

3. RESULTS AND DISCUSSION

The load forecasting is considered from 6.10 to 6.30 in the year 2016 which contains probability CS is given in Tables 1 and 2 and the Cauchy switched parameter CS algorithm is given in Tables 3 and 4. Table 5 represents a comparison of different techniques in STLF [33], [34]. Figures 3 to 8 present the analysis of actual and forecasted load.

Table 1. Load forecasting with probability CS algorithm

Actual load (MW)	Forecasted load (MW)				
	LevyCS	CauchyCS	GaussCS	GammaCS	ParetoCS
943	945	942	941	943	942
914	915	913	912	914	913
907	903	904	905	907	906
875	865	875	875	870	874
873	860	869	870	870	871
872	871	870	869	872	871
931	929	930	929	930	930
976	972	976	973	975	975
1062	1061	1061	1059	1062	1060
1144	1140	1140	1141	1144	1142
1213	1210	1209	1210	1213	1211
1263	1258	1262	1260	1260	1262
1231	1230	1230	1229	1230	1230
1196	1185	1195	1193	1190	1195
1150	1145	1148	1147	1150	1148
1190	1185	1187	1185	1188	1188
1212	1207	1210	1208	1210	1210
1231	1226	1229	1225	1230	1230
1223	1221	1221	1219	1223	1221
1228	1223	1226	1223	1225	1226
1245	1240	1242	1242	1240	1243
1317	1315	1314	1313	1317	1315
1214	1210	1211	1212	1214	1213
1081	1075	1080	1079	1081	1080

Table 2. MAPE with probability CS algorithm

CS algorithms	MAPE (%)
LevyCS	0.407
CauchyCS	0.168
GaussCS	0.264
GammaCS	0.123
ParetoCS	0.127

Table 1 explains the results of the different distribution of the cuckoo search. It also helps to know that, the proposed distribution is good for STLF. The predicted loads are very important for STLF which controls the price of electricity. Table 2 explains the MAPE results of the different distribution of cuckoo search. It also helps to know that, the proposed distribution is good for STLF which also gives less error in forecasted load. It indicates the load stability of different methods.

Table 3 explains the results of the different distribution of the cuckoo search. It also helps to know that, the proposed distribution is good for STLF. The predicted loads are very important for STLF which controls the price of electricity. Table 4 explains the MAPE results of the different distribution of cuckoo search. It also helps to know that, the proposed distribution is good for STLF which also gives less error in forecasted load. It indicates the load stability of different methods. Table 5 explains the MAPE results of different methods used for STLF and it brings high error in STLF as compare to different distribution functions of CS. So the CS is good for STLF which gives less error in forecasted load.

The MAPE of Gamma-CS is 0.123% as compared to the MAPE of Pareto-CS is 0.127% as given in Table 2. So the result of Pareto based CS is better than Levy probability CS. The performance of Levy CS is the least as compared to the other four probability methods. The result of decreasing the switching parameter in CS (CSLD) with respect to MAPE is 0.344% and the result of exponentially increasing parameter in CS (CSEI) with respect to MAPE is 0.389%. So the increasing switching parameter brings good results as compared to constant real switching parameters of CS (CSCo) as given in Table 4 and Gamma-CS is also good as compared to other techniques as given in Table 5.

Table 3. Load forecasting with switching parameter CS algorithm

Actual load	Forecasted load (MW)				
(MW)	CSCo	CSLD	CSLI	CSPI	CSEI
943	909	911	910	911	912
914	908	912	910	912	913
907	895	905	900	905	906
875	849	870	850	872	873
873	855	870	860	870	871
872	855	870	860	869	870
931	915	930	920	929	930
976	961	970	960	970	973
1062	1051	1060	1050	1060	1061
1144	1132	1140	1130	1142	1143
1213	1211	1212	1210	1211	1212
1263	1262	1262	1260	1259	1260
1231	1226	1230	1225	1230	1231
1196	1193	1195	1190	1192	1195
1150	1141	1149	1140	1130	1149
1190	1181	1189	1180	1183	1185
1212	1206	1210	1205	1209	1210
1231	1228	1230	1225	1228	1229
1223	1216	1220	1215	1211	1213
1228	1222	1227	1220	1225	1226
1245	1231	1240	1230	1234	1235
1317	1307	1310	1305	1308	1309
1214	1206	1210	1205	1205	1208
1081	1072	1080	1070	1074	1075

Table 4. MAPE with switching parameter CS algorithm

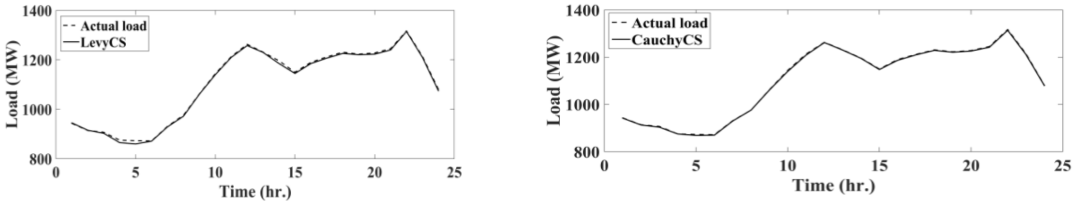
CS algorithms	MAPE (%)
CSCo	0.895
CSLD	0.344
CSLI	0.957
CSPI	0.574
CSEI	0.389

Table 5. MAPE with different algorithms

Algorithms	MAPE (%)
Back propagation neural network (BPNN)	3.42
Genetic algorithm back propagation neural network (GA-BPNN)	3.86
Particle swarm optimization Elman neural network (PSO-ENN)	1.17

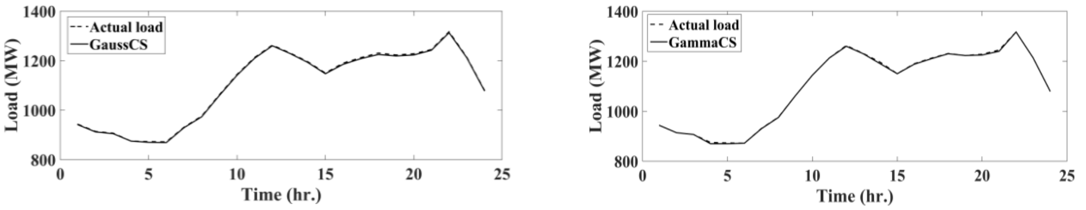
Figure 3 (a) gives the forecasted load of the LevyCS distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variable affect the load in a short interval of time and gives less error in output with the use of MAPE calculation. Figure 3 (b) gives the forecasted load of the CauchyCS distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variable affect the load in a short interval of time and gives less error in output with the use of MAPE calculation.

Figure 4 (a) gives the forecasted load of the GaussCS distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variable affect the load in a short interval of time and gives less error in output with the use of MAPE calculation. Figure 4 (b) gives the forecasted load of the GammaCS distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variable affect the load in a short interval of time and gives less error in output with the use of MAPE calculation.



(a) (b)

Figure 3. Comparison between actual and predicted loads (a) using LevyCS method and (b) using CauchyCS method

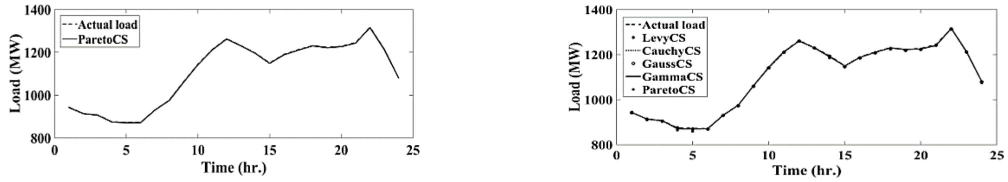


(a) (b)

Figure 4. Comparison between actual and predicted loads (a) using GaussCS method and (b) using GammaCS method

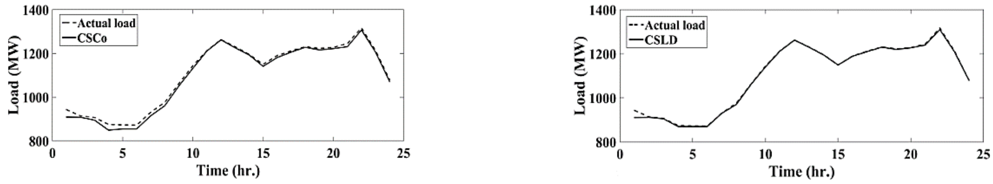
Figure 5 (a) gives the forecasted load of the Pareto distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variable affect the load in a short interval of time and gives less error in output with the use of MAPE calculation. Figure 5 (b) gives the forecasted load of the different distribution of cuckoo search. These methods are bringing good accuracy and maintain load stability. These are robust methods which include all variable affect the load in a short interval of time and give less error in output with the use of MAPE calculation.

Figure 6 (a) gives the forecasted load of the CSCo distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variable affect the load in a short interval of time and gives less error in output with the use of MAPE calculation. Figure 6 (b) gives the forecasted load of the CSLD distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variable affect the load in a short interval of time and gives less error in output with the use of MAPE calculation.



(a) (b)

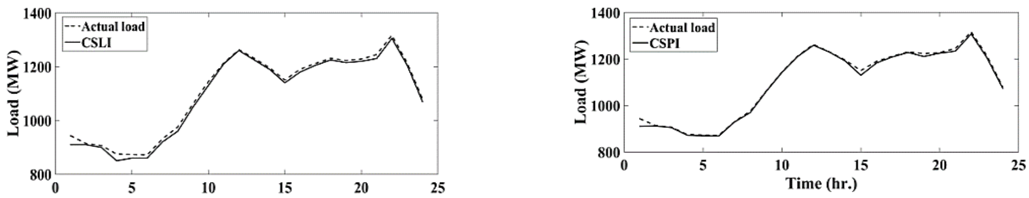
Figure 5. Comparison between actual and predicted loads: (a) using ParetoCS method and (b) using different methods



(a) (b)

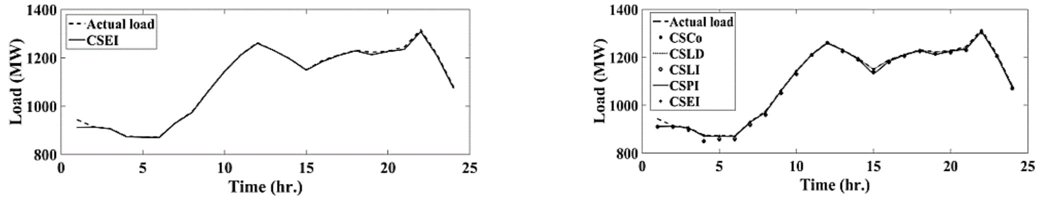
Figure 6. Comparison between actual and predicted loads: (a) using CSCo method and (b) using CSLD method

Figure 7 (a) gives the forecasted load of the CSLI distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variable affect the load in a short interval of time and gives less error in output with the use of MAPE calculation. Figure 7 (b) gives the forecasted load of the CSPI distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variable affect the load in a short interval of time and gives less error in output with the use of MAPE calculation. Figure 8 (a) gives the forecasted load of the CSEI distribution of cuckoo search. This method brings good accuracy and maintains load stability. It is a robust method which includes all variable affect the load in a short interval of time and gives less error in output with the use of MAPE calculation. Figure 8 (b) gives the forecasted load of the different distribution of cuckoo search. These methods are bringing good accuracy and maintain load stability. These are robust methods which include all variable affect the load in a short interval of time and give less error in output with the use of MAPE calculation.



(a) (b)

Figure 7. Comparison between actual and predicted loads (a) using CSLI method and (b) using CSPI method



(a) (b)

Figure 8. Comparison between actual and predicted loads (a) using CSEI method and (b) using different methods

4. CONCLUSION

The optimization theory and its importance in the engineering problem are described in this manuscript. The different nature's inspired algorithms like PSO, DE and SA are discussed with their work. Here we got good results in efficient random work of the CS algorithm and maintained the balance between the local and global random walk as compared to other algorithms. It is also reviewed the work of NN for the STLF. The CS for improved BP is also discussed. The probability distribution and dynamic switching parameters are also discussed for the improvement of CS. For the electric load forecasting, 4-25-1 FFNN is used. The Gamma probability rings good results as compared to other methods and its error is 0.123%. The average error of Pareto and Levy based CS is 0.127% and 0.407%. The average error of decreasing switching parameter is 0.344% in CS and it is good as compared to exponentially increasing parameters i.e. 0.389%.

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